Missouri Sex Offender Fail to Register Predictive Model

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INTRODUCTION

The criminal justice system treats offenders who have committed crimes of a sexual nature much differently than virtually any other type of offender (Edwards & Hensley, 2001). Due to the especially heinous nature of crimes committed by sex offenders, preventing reoffending is especially important to ensuring the safety of the public. A broad scope of legislation has been passed with the goal of controlling the sex offender population. In 1989, the Federal government passed the Jacob Wetterling Crimes Against Children and Sexually Violent Offender Registration Act (42 USC 14071) that mandated community registration for sex offenders. This act was initially amended to include mandatory dissemination of registry information (Megan's Law), lifetime registration for serious offenders and recidivists (Pam Lychner Act), and was eventually replaced by the Adam Walsh Act. The Sex Offender Registration and Notification Act (SORNA), Title I of the Adam Walsh Act, became law in 2006. SORNA established baseline criteria for jurisdictions to follow pertaining to their registration and monitoring of sex offenders. Specifically, SORNA was created to achieve a greater degree of standardization and uniformity across jurisdictions with respect to offender registration and notification. This standardization ensures that records remain up-to-date when individuals change residences or jobs, and when they travel. Many states have faced challenges in substantially implementing SORNA and to date only 19 states, including Missouri, have become SORNA compliant (Government Accountability Office, 2013).

An emerging body of literature concerning the efficacy of registration requirements suggests they have done little to reduce sexual reoffending (Tewksbury & Jennings, 2010; Huebner et al., 2014). By comparison, much less is known about the factors that influence compliance with these laws among sex offender populations. With few exceptions (Levenson,

Ackerman, & Harris, 2014), the extant literature has only started to focus on the factors associated with an increased likelihood of absconding or violating registration agreements. The current project aims to determine the characteristics most useful in predicting compliance with sex offender registry requirements among a sample of registered sex offenders in Missouri.

REVIEW OF RELEVANT LITERATURE

There is an extensive, nuanced body of literature predicting risk for reoffending among sex offenders. Due to the unique nature of sexual offending, risk assessments designed specifically to predict sexual reoffending risk are a necessity and have been validated largely for correctional populations (e.g. RASOR, Static-99). In addition to predicting future sexual offending, there is an increasing desire among practitioners to predict noncompliance with conditions of community supervision, including registration requirements. Technical violations often signal changes in lifestyle conditions, such as deteriorating mental health conditions or increases in substance abuse or dependence (Bushway & Apel, 2012). While technical failures may not be direct indicators of one's intention to begin reoffending, they are likely precursors to other forms of failure.

Criminal justice staff increasingly relies on risk instruments to aid practitioners in decision making with the goal of estimating the likelihood of future criminal and risky behavior. While also used in sentencing decisions, such risk tools are most commonly used to assess the amount and type of supervision required to attain the compliance of individuals under community supervision. Numerous risk instruments presently exist to predict each of a variety of behaviors (e.g., violent reoffending, sexual reoffending, and general reoffending). While risk measures of sexual reoffending are rather common, there are, at present, no tools designed to predict technical violations for sex offenders.

A number of risk tools for sexual behavior and recidivism have been developed that can help guide the development of instruments for use with this population. Hanson and colleagues (Hanson, 1998; Hanson & Bussiere, 1998; Hanson & Thornton, 2000) have developed the most seminal work in the area of assessments of sexual reoffending risk. Hanson and Bussiere (1998) conducted the initial meta-analysis focused on the factors predictive of recidivism in a sample of sex offenders. Importantly, this research finds factors predicting sexual offending to be largely different from the factors forecasting general recidivism. The best predictors of sexual recidivism were: a history of sexual offending and deviant sexual preferences. These findings necessitated treating sexual recidivism as distinct from general recidivism, thereby necessitating sex-offender specific risk models.

While there is an expansive literature focused on sexual recidivism, little research has been conducted on failure to register (FTR). The initial research conducted on FTR assessed whether it was a useful predictor of recidivism; studies suggest that failure to register is not predictive of subsequent sexual reoffending (Duwe & Donnay, 2010; Levenson, Letourneau, Armstrong, & Zgoba, 2010). For example, Duwe and Donnay (2010) found that having a prior FTR conviction was not significantly related to either sexual or general recidivism; however it was predictive of a future FTR. Similarly, Levenson and her colleagues (2010) did not find a significant association between FTR and sexual recidivism, nor was FTR linked with timing of failure (Levenson et al., 2010; Zgoba & Levenson, 2012).

More recent work has considered the factors associated with FTR and absconding (Levenson, Ackerman, & Harris, 2014). Some of these studies have suggested that factors predictive of FTR are similar to those which predict general, as opposed to sexual, recidivism (Zgoba & Levenson, 2012; Levenson, Ackerman, & Harris, 2014). FTR has been shown to be

significantly related to general criminogenic factors like criminal history, age, and prior FTR. Specifically, sex offenders with more lengthy criminal histories and previous instances of FTR, as well as younger RSOs, were more likely to subsequently fail to report or stay current on registration requirements. For example, a study in New York found that the offenders who were most likely to FTR were those who were young and had a greater number of prior convictions, although the differences in criminal history were not substantially large, and included sexual and non-sexual offenses (Levenson, Sandler, & Freeman, 2012). Additionally, Zgoba and Levenson (2012) found that younger sex offenders in New Jersey with more prior sexual arrests were more likely to fail to register; however, number of prior non-sexual arrests was not predictive of FTR. Instead, FTR appeared to be associated with victim characteristics. Sex offenders who victimized adult females and assaulted strangers were significantly more likely to be arrested for FTR (Zgoba & Levenson, 2012). Similarly, work in Florida suggests that individuals with minor victims and prior sexual offenses are more likely to FTR (Levenson, Ackerman, & Harris, 2014). Overall, a clear array of risk variables associated with FTR have been identified, but the extant literature is yet to assess simultaneously how non-sexual prior offending and present life circumstances, such as social support and employment, affect the likelihood of noncompliance.

MISSOURI SORNA

As noted, the current study first assesses the factors related to sex offender FTR in Missouri with the ultimate goal of developing a composite risk instrument for use by law enforcement personnel. Missouri is well-suited for a study of this type as it was among the first states to pass registration legislation in January 1995 and is currently SORNA compliant. The law requires all offenders convicted of criminal sexual conduct to register with the Missouri State Highway Patrol (MSHP). Offenders who victimized adults must register and verify their

address every six months and offenders who assaulted juveniles or have been deemed persistent sexual offenders must register every 90 days. Missouri requires lifetime registration for all sex offenders. In August 2004, the registration laws were extended to prohibit sex offenders from living within 1,000 feet of a school or childcare facility ("Missouri revised statues," 2006). In addition, sex offenders are also prohibited from working or loitering within 500 feet of a school or childcare facility. The MSHP maintains a centralized data system, and over 18,000 individuals are listed on the registry. In Missouri, sex offenders represent 15% of the institutional population and two percent of probationers. Each year, approximately 900 sex offenders are released from prison on parole, and 250 are sentenced to a term of probation (Missouri Department of Corrections, 2015).

The Sex Offender Registry was created in response to the Missouri Legislature's resolution to facilitate public access to available information about persons registered as sexual offenders. Information is collected by the sheriff in each county in which an offender resides and is submitted to the Missouri State Highway Patrol for compilation. The MSHP Criminal Justice Information Services (CJIS) has a very advanced data system capability, and the data in the registry are updated on a daily basis. MSHP CJIS staff works with the MSHP Statistical Analysis Center (SAC) to continue to enhance the computing capabilities of the office and to disseminate developments in public policy-relevant information in the state.

DATA AND MEASURES

The purpose of this research was to establish the factors related to sex offender noncompliance and absconding for registered sex offenders (RSOs) in Missouri. Individuals (n=18,010) on the Missouri Sex Offender registry between March 9, 2014 and April 6, 2015

were included in the study and followed during the same period. The initial registration date of offenders analyzed ranges from January 1994 and April 2015.

DEPENDENT MEASURES

Failure to register served as the dichotomous, dependent variable in the analysis and includes individuals who were classified as noncompliant for registry requirements and individuals deemed absconders (1= noncompliant; 0= compliant). While absconding and failure to register can reflect different behaviors, they were combined in the current study because of the relatively low (roughly 1%) proportion of absconders in the data set. In addition, there was wide variation in the use of the absconder code. The MSHP automatically codes someone as non-complaint if their paperwork is overdue. Conversely, local agencies are responsible for classifying someone as an absconder.

In addition, we included a dichotomous *incarceration* measure (1=individual was incarcerated during the study period and did not have a record of noncompliance; 0=individual did not have a record of incarceration). Data on the nature of the behavior that precipitated incarceration was not available; however, this measure was included as a proxy for recidivism and problem-behavior. Including this measure in the multinomial models provided additional validity checks on the predictive measures. In the multivariate regression models presented, one set of analyses examined solely the factors predictive of noncompliance and excluded incarcerated offenders. A second set of analyses (*see* Table 3) uses multinomial regression to estimate the factors related to both noncompliance and incarceration.[1]

[1] Additionally, offenders who moved out of state (n=5,654) or are deceased (n=1,986) were excluded from the bivariate and multivariate analyses, as this was not an outcome central to the purpose of the current work.

INDEPENDENT MEASURES

Several demographic measures were used as controls including sex (*female*=1), race (*Black*=1), and *age* (1=under 40 years at time of first registration). The majority of the sample was male (97%) and Caucasian (79%). Over half (59%) of the sample was under forty years of age at the time of placement on the sex offender registry, (see Table 1 for demographic information).

Table 1: Bivariate Statistics n=18,010

	Compliant (n=14,266)	Noncompliant (n=1,437)	Incarcerated (n=2,307)	Total (n=18,010)
Offender-Level Factors				
Female	3.5	2.5	1.6	3.1
Black	17.4	36.5	25.2	19.9
Age under 40	56.7	64.2	71.8	59.2
Juvenile Offender	1.7	2.9	3.3	2.0
Employed	79.0	68.6	61.2	75.9
Valid Driver's License	65.4	17.0	11.0	54.5
Registration Interval	89.8	83.9	86.5	88.9
Prior Incarceration on Supervision	28.5	36.3	70.9	34.5
Family Emergency Contact	82.6	65.6	64.1	78.9
Male Victims	15.0	11.6	14.1	14.6
Victim under 18	85.5	78.7	81.0	84.4
Victim was a Stranger	42.6	55.8	49.8	44.6
Prior Offense(s) Include				
Forcible Rape or Sodomy	42.5	44.7	53.8	44.1
Sexual Assault	17.2	18.6	16.8	17.2
Child Molestation	12.3	9.0	15.0	12.3
Entice/Endanger Minor	3.0	2.2	3.0	2.9
Pornography	5.2	1.7	3.0	4.7
Sexual Misconduct	8.5	7.7	9.0	8.5

Prior Sexual Conviction	23.9	27.6	53.5	27.9
Prior Non-Sexual Convictions				
None	75.0	53.4	45.4	69.5
One	9.7	12.7	12.4	10.3
Two	11.9	25.1	26.5	14.8
Three or more	3.5	8.9	15.7	5.5
Location				
St. Louis County	9.7	2.5	2.4	8.2
St. Louis City	7.9	24.4	2.0	8.5
Kansas City	15.4	23.0	2.7	14.4
Greene County	4.5	2.2	1.0	3.9
Boone County	2.0	2.9	0.4	1.9

Criminal history has also been associated with registration noncompliance (Levenson, Ackerman, & Harris, 2013). Approximately 20% committed forcible rape or sodomy while an additional sixteen percent were convicted of statutory rape or sodomy. The remaining offenders were convicted of sexual assault (17%), child molestation (11%), endangering the welfare of a child (3%), pornography related offenses (4%), and sexual misconduct (8%). The majority of the sample (73%) did not have any prior non-sexual felony convictions. A very small proportion of the sample had a juvenile record (2%). Finally, two measures of criminal history were included in the model: *prior sexual conviction* (1=one or more prior sexual convictions, excluding the offense requiring registration; 0= prior sexual convictions) and *prior non-sexual felony convictions* (1= one, 2=two, 3= three or more; 0=no prior non-sexual felony convictions).

In addition, we captured differences in registration compliance requirements. RSOs are required to check-in and confirm their registry information in order to remain compliant, but for multiple reasons, the time span between registration check-ins varies by offender. Pursuant to Missouri Statute 589.414.1, predatory and persistent offenders, as well as those who offended against a victim under 18 or have previously failed to register are required to check-in every

three months. Most offenders (89%) are required to check-in every 90 days while the remaining eleven percent of the sample has a six month *registration interval* (1=six months; 0= 90 days).

Some emerging research suggested that relationships, employment, and being embedded in conventional society are associated with lower rates of recidivism (Visher, LaVigne, and Travis, 2004). Unique to this research, we included three measures of current life circumstances in our analyses: *employment*, *driver's license*, and *immediate family emergency contact*. In total, 53% of the RSOs in the sample were *employed* (1= employment address was listed in registration file; 0=no employment address listed). Drawing from drug treatment compliance literature (Sung et al., 2004), RSO Driver's license status (1=individual had current, valid driver's license; 0=license was suspended or not active) was included to measure the extent to which the RSO has an organized lifestyle. In the full sample, 39% percent of RSOs had a valid driver's license. Social support in the community was operationalized using the relationship to an RSO's emergency contact. If offenders listed an *immediate family member* as their emergency contact, they were coded as having social support in the community; this was the case for 69% of the sample (1= spouse, significant other, or parent as emergency contact; 0=child, sibling, other, or unknown).

Victim characteristics were also a central part of the predictive model as prior research suggested individuals who offend against minor victims are more likely to comply with registry requirements (Hanson & Morton-Bourgon, 2005; Levenson, Ackerman, & Harris, 2013). We examined three victim characteristics including victim sex (1=*male victim*; 0=female), victim age (1=*victim under 18*; 0=victim 18 or older), victim offender relationship (1=*victim was a stranger*; 0= victim was known to the offender). The vast majority of offenders (85%) had female victims. In total, 35% of the sample offended against a minor victim, and 49% of RSOs

committed offenses against a stranger or a person with whom the relationship type was unknown.

There is ample theoretical and empirical evidence to suggest that enforcement can vary significantly across agencies. Therefore, we included the jurisdictions with the five largest populations of RSOs as dichotomous controls: Kansas City (12%), St. Louis City (7%), St. Louis County (6.5%), Greene County (3%), and Boone County (1.5%).

METHODS AND ANALYSES

PREDICTIVE MODELS

The analysis plan was comprised of three distinct but related phases. First, a series of logistic regressions were used to predict noncompliance and incarceration (see Tables 2 and 3). The research team iteratively built the models, with the first phase of models including offender-level factors alone. In the second models, offense and victim characteristics were added. The final set of models contains geographic information pertaining to the county in which the offender is registered. Next, multinomial regression was used to model the outcomes of noncompliance and incarceration simultaneously, and compare both to the reference category of compliant offenders.

In the full multivariate models, the majority of specified covariates were significant predictors of registration noncompliance (Table 2). Registrants who are younger, of minority race, and register every six months were more likely to be noncompliant. Conversely, offenders who noted linkages to immediate family members were half as likely to be noncompliant, and employment was also associated with a reduced risk of failure. A valid driver's license was the factor with the greatest effect size, reducing the likelihood of non-compliance by 85%.

Shifting the focus to victim and offense characteristics, registrants with a prior offense against a minor victim were nearly 20% less likely to be noncompliant, and convictions for pornography offenses and sexual assault were also negatively and significantly associated with noncompliance. Individuals charged with forcible rape or sodomy were more likely to be noncompliant, and RSOs who committed their register able sex offense against a stranger or unknown victim were 40% more likely to fail to comply. Prior convictions for sexual and non-sexual offenses were also significantly and positively associated with non-compliance. As anticipated, jurisdictions had varying levels of non-compliance. St. Louis City, Kansas City, and Boone County had the highest non-compliance rates, while rates were much smaller in Greene and St. Louis Counties.

Table 2: Logistic Regression Models Predicting Registration Noncompliance

	Model 1		Model 2		Model 3	
	Odds Ratio	Std. Error	Odds Ratio	Std. Error	Odds Ratio	Std. Error
Independent Variables						
Female	0.78	0.14	0.91	0.17	0.90	0.17
Black	1.77***	0.11	1.56***	0.10	1.39***	0.11
Age	1.43***	0.09	1.45***	0.09	1.50***	0.10
Juvenile Offender	1.19	0.22	1.16	0.22	1.12	0.22
Employed	0.82***	0.05	0.79***	0.05	0.82***	0.06
Driver's License	0.13***	0.01	0.14***	0.01	0.14***	0.01
Registration Interval	1.17*	0.10	0.82**	0.07	0.82**	0.08
Prior Incarceration on Supervision	1.01	0.06	0.97	0.07	0.88*	0.06
Immediate Family Member	0.49	0.03	0.49***	0.03	0.46***	0.03
Male Victim	--		0.90	0.09	0.85*	0.08
Victim Under 18	--		0.78***	0.07	0.80**	0.07
Forcible Rape or Sodomy Offense	--		1.27***	0.10	1.23**	0.10
Child Molestation	--		0.98	0.12	0.97	0.12
Pornography	--		0.60*	0.17	0.60*	0.17
Sexual Assault	--		0.82**	0.07	0.83**	0.07
Relation to Victim, Unknown Relation	--		1.38***	0.09	1.39***	0.09

Prior Sexual Conviction	--		1.26***	0.10	1.26***	0.11
Prior Non-Sexual Felony Conviction	--		1.28***	0.04	1.28***	0.04
St. Louis County	--		--		0.17***	0.03
St. Louis City	--		--		2.16***	0.20
Kansas City	--		--		1.74***	0.14
Greene County	--		--		0.64**	0.12
Boone County	--		--		1.57**	0.30
Log-likelihood		-3742.92		-3891.10		-3716.58

* p<.10; ** p<.05; *** p<.01

As a further test of the robustness of the models, a multivariate multinomial regression was estimated to differentiate effect of the FTR and incarceration models. As shown, there were many similarities between models (see Table 3). Individuals of minority race, younger registrants, and those with more involved criminal histories were more likely to FTR and to be incarcerated. Stranger victims and forcible rape or sodomy changes was also positively associated with FTR and incarceration. A valid driver's license and contact with immediate family reduced the likelihood of FTR and incarceration. However, a few important differences emerged. Individuals with male and/or younger victims were more likely to be incarcerated; opposite of what was observed in the FTR model. Similarly, prior stays of incarceration increased subsequent incarceration, and individuals with prior sexual convictions were negatively associated with incarceration but positively associated with FTR. Finally, individuals sentenced in the largest counties were much less likely to be incarcerated; whereas, there was substantial county-wide variation for the FTR model.

Table 3: ***Logistic Regression Models Predicting Registration Noncompliance & Incarceration***

	Model 1		Model 2		Model 3	
	Odds Ratio	Std. Error	Odds Ratio	Std. Error	Odds Ratio	Std. Error
NONCOMPLIANT (n=1,437)						
Female	0.81	0.15	0.95	0.18	0.93	0.18
Black	1.77***	0.11	1.54***	0.10	1.41***	0.11

Age	1.42***	0.09	1.43***	0.09	1.49***	0.10
Juvenile Offender	1.19	0.22	1.14	0.22	1.07	0.21
Employed	0.83***	0.06	0.80***	0.05	0.82***	0.06
Driver's License	0.13***	0.01	0.14***	0.01	0.14***	0.01
Registration Interval	1.16*	0.10	0.81**	0.07	0.80**	0.08
Prior Incarceration on Supervision	1.02	0.06	1.00	0.07	0.93	0.06
Immediate Family Member	0.49***	0.03	0.51***	0.03	0.47***	0.03
Male Victim	--		0.89	0.08	0.84*	0.08
Victim Under 18	--		0.76***	0.07	0.77***	0.07
Forcible Rape or Sodomy Offense	--		1.23***	0.10	1.19**	0.10
Child Molestation	--		0.99	0.12	0.96	0.11
Pornography	--		0.65	0.18	0.66	0.19
Sexual Assault	--		0.83***	0.07	0.84**	0.07
Relation to Victim, Unknown Relation	--		1.37***	0.09	1.37***	0.09
No Prior Sexual Conviction	--		1.23**	0.10	1.23**	0.10
Prior Non-Sexual Felony Conviction	--		1.28***	0.04	1.28***	0.04
St. Louis County	--		--		0.18***	0.03
St. Louis City	--		--		2.19***	0.19
Kansas City	--		--		1.79***	0.14
INCARCERATED (n=2,307)						
Female	0.60***	0.11	0.58***	0.11	0.60***	0.12
Black	0.88**	0.05	0.75***	0.05	1.73***	0.13
Age	1.91***	0.11	1.86***	0.11	1.66***	0.10
Juvenile Offender	1.36*	0.21	1.40**	0.22	1.54**	0.26
Employed	0.53***	0.03	0.51***	0.03	0.60***	0.04
Driver's License	0.10***	0.01	0.11***	0.01	0.10***	0.01
Registration Interval	1.14	0.09	1.00	0.09	1.12	0.11
Prior Incarceration on Supervision	4.62***	0.26	3.76***	0.22	3.93***	0.25
Immediate Family Member	0.38***	0.02	0.38***	0.02	0.36***	0.02
Male Victim	--		1.20**	0.10	1.28***	0.11
Victim Under 18	--		1.25***	0.09	1.30***	0.10
Forcible Rape or Sodomy Offense	--		1.16*	0.09	1.24***	0.10
Child Molestation	--		1.14	0.10	1.30***	0.12
Pornography	--		0.81	0.15	0.88	0.17
Sexual Assault	--		0.85**	0.06	0.76***	0.06
Relation to Victim, Unknown Relation	--		1.46**	0.08	1.57***	0.09
No Prior Sexual Conviction	--		0.71***	0.06	0.64***	0.06
Prior Non-Sexual Felony Conviction	--		1.50***	0.04	1.48***	0.04
St. Louis County	--		--		0.07***	0.01
St. Louis City	--		--		0.07***	0.01
Kansas City	--		--		0.09***	0.01

* p<.10; ** p<.05; *** p<.01

Given the variation in FTR rates by county, a supplemental model was estimated to include only those individuals who were processed in the five most populous counties. The

models did not vary substantively from those estimated in the full FTR model. The supplemental analyses further supported the validity of the models.

RISK ASSESMENT MODELS

The final portion of the project involved using the multivariate models to develop a composite risk assessment with the goal of classifying RSOs into risk levels of registry noncompliance. Ten items were captured on the risk assessment instrument created by the research team. The full models were winnowed down to the ten items using two criteria: strength of the multivariate predictor and theoretical relevance (e.g., minor victim, prior sexual offense convictions). Next, the effect sizes from the multiple regression models were used to assign appropriate weights to each of the items included on the risk instrument (see Table 4).

Items that increase risk of noncompliance were scaled in the same manner that they were in the multiple regression models. Conversely protective factors, or those that reduce the likelihood of noncompliance, were reverse coded. In reverse coding these variables, were able to simplify interpretation of the risk score; higher risk scores meant greater likelihood of noncompliance. The weights were assigned based on the odds ratios from the regression models. Since protective factors were reverse coded, the inverse of the odds ratio represents the weight assigned to these variables. The included risk factors had the following weights in the risk assessment: age at initial registration (1.4); present age (1.0); register able offense of forcible rape or sodomy (1.7); offending against an unrelated victim (1.8); any prior sexual conviction (1.0); and number of prior non-sexual felony convictions (1.5). The remaining four items on the risk tool are protective factors and have been assigned the following weights: any prior male victim (1.0); any prior minor victim (1.5); having social support in the community (3.0); and having a driver's license as a measure of an organized lifestyle (5.0). Once all ten items were

coded in a uniform direction and the corresponding weights were assigned to the individual factors, an overall risk score was computed for each offender. The continuous risk score had a possible range of zero to 20.4.[2]

Table 4: Risk Assessment Items

Item #	Item Description	Cutoff Groups	Risk/Protective	Weight
1	Age at First Registration Date	0 – 40 and older 1 – under 40	Risk	1.4
2	Present Age	0 – 26 or older 1 – 25 or younger	Risk	1.0
3	Forcible Rape/Sodomy	0 – No 1 – Yes	Risk	1.7
4	Unrelated Victim	0 – No 1 – Yes	Risk	1.8
5	Any Male Victim	0 – Yes 1 – No	Protective	1.0
6	Any Minor Victim	0 – Yes 1 – No	Protective	1.5
7	Any Prior Sexual Felony Conviction	0 – 0 1 – 1 or more	Risk	1.0
8	Prior Non Sexual Felony Convictions	0 – 0 1 – 1 2 – 2/4 3 – 5 or more	Risk	1.5
9	Social Support in Community	0 – Yes 1 – No	Protective	3.0

[2] For the driver's license risk item, using the odds ratios from regression models would have resulted in an even larger weight than was assigned. To prevent a single risk factor from exerting too much influence, we reduced this weight accordingly. A weight of five was used because this meant an individual without a license could still be in the minimal risk group, if no other risk factors were present.

10	Driver's License	0 – Yes 1 – No	Protective	5.0

ROC ANALYSIS

Finally, to develop the risk assessment tool and to evaluate its efficacy, this study utilized relative operator characteristic (ROC) analysis (Rice and Harris, 1995; Mossman, 2013). One attractive feature of this method for validating assessments is its relative parsimony. ROC analysis provides manageable statistics to indicate the level at which risk cut-offs can adequately identify true-positives while minimizing the number of false-positives. ROC analysis primarily focuses on the plotted values which make up the ROC curve. These plotted values are composed of two important features of risk assessment: specificity and sensitivity. Sensitivity concerns the accuracy of identifying those who will become non-compliant (true positives), while specificity concerns the accuracy of identifying those who will remain compliant (true negatives) (Metz, 1978). Our risk assessment tool, then, will be an attempt to maximize the probability of capturing those who will become non-compliant (true positives) while minimizing the number of individuals identified as high-risk yet remaining compliant (false positives). By plotting sensitivity and specificity, we can evaluate the successfulness of this endeavor. This is typically done through use of the AUC (area under the curve) statistic. If a test does no better than random chance at identifying true positives, the plotted values of specificity and sensitivity would form a straight diagonal, and have a corresponding AUC value of .50. Thus, we can determine how much better a tool is performing over chance through the use of the AUC. Most simply, this space can be interpreted as the probability of a randomly selected non-compliant offender scoring higher on the risk assessment than a randomly selected compliant offender.

In the current analysis the composite risk score was validated using the ROC analysis and produced a curve with a corresponding AUC value of 0.777. This means that if a compliant offender and a non-compliant offender were each randomly selected from the sample, the non-compliant offender would have a higher risk score approximately 78% of the time. Once these diagnostic measures were computed for risk as a continuous measure, the next task was to divide the risk score into meaningful risk groups or levels.

The risk score was cut into levels using ROC techniques. That is, cutoff points were drawn to form risk categories at the numerical values where size of the gap between sensitivity and specificity were simultaneously the largest. The score was divided into four risk groups (see Table 5). A risk score of less than six meant an RSO was classified as minimal risk. RSOs with risk scores between six and ten were classified as low risk. Offenders with scores between 10 and 13 were classified as moderate risk and RSOs with risk scores above thirteen comprise the highest risk level. Roughly thirty percent of the sample was assessed as posing a minimal risk of noncompliance, while twenty-five percent fell into both the low and moderate risk categories, and the remaining 20% were estimated to have a relatively high risk of noncompliance.

Table 5: Risk Assessment and Prediction

Prevalence Rate	Frequency	Percent	Score Range
Minimal	7,213	28.79	0 – 5.9
Low	6,512	25.99	6 – 9.9
Moderate	6,714	26.79	10 – 13.1
High	4,619	18.43	13.2 – 21

When considering risk by compliance, the model continued to fare well. Of the 7,213 offenders in the minimal risk group, only 153 (2%) were noncompliant. 6,512 offenders were classified as low risk; within this group, 303 (7%) failed to remain in compliance with registration requirements. The moderate risk group contained an additional 6,714 offenders.

Within this group, only 2,740 had valid outcome data because many had moved out-of-state or were incarcerated. Of those with a present outcome measure, 464 (17%) were noncompliant. Finally within the portion of the high risk group containing a valid outcome measure, 517 of 1,663 (31%) were noncompliant with requirements.

Table 8. Risk Scores by Compliance Rate

Bivariate Relationship	Frequency	Percent (Compliant)
Minimal		
Compliant	6,927	**97.84**
Noncompliant	153	2.16
Low		
Compliant	3,917	**92.82**
Noncompliant	303	7.18
Moderate		
Compliant	2,276	**83.07**
Noncompliant	464	16.93
High		
Compliant	1,146	**68.91**
Noncompliant	517	31.09

Receiver-operator-characteristic (ROC) curves were used to assess the ability of this risk classification scheme to predict registration noncompliance. The (AUC) in ROC analysis is the metric by which the prediction is gauged. Typically, scores above 0.70 are viewed as adding significant predictive value. First, a ROC curve was generated for the continuous risk measure (Figure 1). The continuous measure produced an AUC value of 0.777, suggesting the risk score is a useful measure of noncompliance risk. As discussed, the divisions in the risk score to produce risk groups are placed where the gap between sensitivity and specificity are the largest.

These gaps can be seen graphically in Figure 1; the corresponding points in Figure 2 show the curve with created groups.

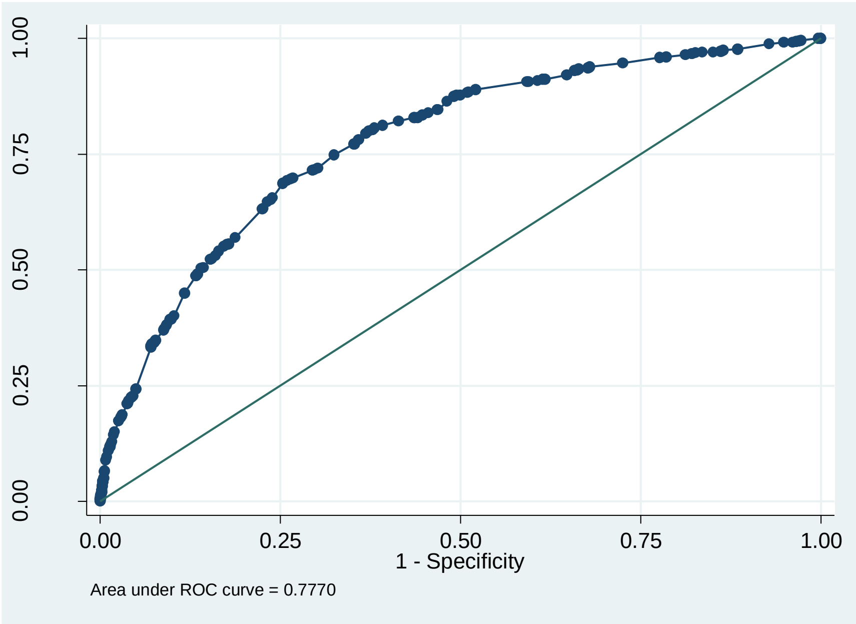

Figure 1: ROC Analysis of Risk Score

The four group classification and prediction approach outlined above produced an AUC value of 0.773 (Figure 2), suggesting that it is a useful metric for measuring a given RSO's likelihood of registration noncompliance or absconding. From a psychometric standpoint, the risk groups cannot produce a higher AUC value than the continuous measure. The fact that the AUC values for the continuous score and risk level were substantively the same provides strong evidence that the cutoff points were drawn appropriately. The practical interpretation for an AUC value of .773 is virtually the same as it is for the risk score. If one were to randomly select a compliant and a non-compliant offender, the non-compliant offender would be in a higher risk level 77% of the time.

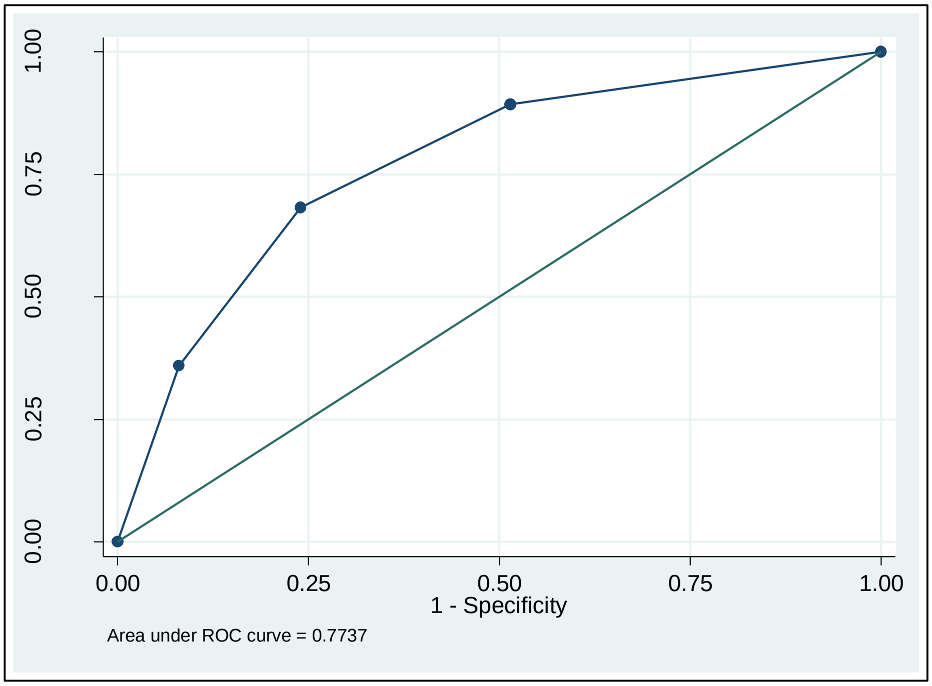

Figure 2: ROC Analysis of Risk Groups

CONCLUSION AND FUTURE RESEARCH

The current research adds to the growing body of literature focused on sex offender noncompliance and failure to report in a number of substantive areas. Several important results emerged. As anticipated, individuals who were younger at the time of first registration and at the time of the study were more likely to fail to register as were individuals convicted of forcible rape and those persons with prior convictions for sexual and non-sexual crimes. Also, individuals with adult and/or female victims had a higher likelihood of failure. In addition, the this study introduced several new variables to the account for social support in the community by looking at whether an offender has a family member listed as their emergency contact; offenders with this protective factor appear to be less likely to become noncompliant. Additionally, knowledge of an offender's current driver's license status was used to assess the degree to which an offender

had an organized lifestyle. RSOs with a valid driver's license pose less risk of becoming noncompliant. Although beyond the scope of the current work, there were many similarities between the significant measures associated with FTR and incarceration; however, the variation in the models suggests the potential need for risk instruments that predict FTR from more traditional measures of recidivism, such as re-incarceration.

Finally, using ROC analysis, the research team were able to measure the cumulative effect of the most salient risk factors to develop a risk assessment and classification instrument. Meaningful differences in the likelihood of noncompliance emerged between each of the four risk categories created, and the measures of risk are validated using advanced statistical techniques. Overall, the risk instrument has the potential to be a valuable tool for law enforcement and other criminal justice actors, armed with only information from the sex offender registry. This tool can be completed quickly in the field and with little training.

This research study was certainly not without limitations. First, the data only include legally-relevant variables. Although this study introduced a social support measure, a more comprehensive measure of an RSO's social support in the community would have been ideal. Additionally, since both prior research and the present study suggest that a disorganized lifestyle increases the risk of noncompliance, a measure of lifestyle disorganization that includes more aspects of an individual's life would be beneficial. From one perspective, the readily accessible nature of driver's license information likely increases the utility of this measure for front-line workers. Conversely, a more multifaceted measure of disorganization would likely improve the ability of the risk assessment to classify offenders. In addition, since full street addresses were not available, there was no way to assess how often an offender moved. Changing residences may be related to noncompliance or absconding but this could not be thoroughly assessed.

Overall, this analysis provided an important first step in better understanding individual and composite risk of FTR. Prior research suggested that FTR and other problem behaviors can signal eventual criminal behavior. Understanding signals for sex offenders is particularly important given their low base rate of official recidivism. In addition, developing a risk instrument to be used by law enforcement, or any criminal justice actor with access to the registry, broadens the usefulness of the tool. This type of tool is particularly important given that individuals are often only under correctional supervision for a few years and then the burden of compliance management is t shifted to law enforcement. Continuing this line of research will likely have practical implications for criminal justice agencies and will facilitate a more nuanced understanding of sex offender behavior.

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Appendix A: Previously Used Predictors for Sex Offender Behavior

Independent Variable	**Outcome Variable Being Predicted**				
	General Recidivism	Sexual Recidivism	Violent Recidivism	Failure to Register	Absconding
Prior Sexual Offenses	3	1		3; 4; 5; 6	4
Instant Offense Type				3; 6	
Criminal History	3	1		3; 5; 6	
Sexual Preference for Children		1		3; 4; 5	4
Deviant Sexual Preferences		1; 2			
Antisocial Orientation/Personality	2	1; 2	2		
Age		1		3; 5; 6	
Antisocial Peers	1		1		
Procriminal Attitudes	1		1		
Prior failure to register charge/conviction	3	3		4; 6	4
Failure to complete treatment		1			
Never Married		1		5	
Unrelated Victims		1			
Male or Child Victims		1		5	
Sexual Attitudes	2	2	2		
Stranger Victims				5	
# of Technical Violations				5	

[1] Hanson & Bussière, 1998; [2] Hanson & Morton-Bourgon, 2005; [3] Levenson, Letourneau, Armstrong, & Zgoba, 2010; [4] Levenson, Ackerman, & Harris, 2013; [5] Zgoba & Levenson, 2012; [6] Levenson, Sandler, & Freeman, 2012